

# Package ‘vtreat’

January 20, 2018

**Type** Package

**Title** A Statistically Sound 'data.frame' Processor/Conditioner

**Version** 1.0.2

**Date** 2018-01-20

**URL** <https://github.com/WinVector/vtreat/>,  
<https://winvector.github.io/vtreat/>

**BugReports** <https://github.com/WinVector/vtreat/issues>

**Maintainer** John Mount <jmount@win-vector.com>

**Description** A 'data.frame' processor/conditioner that prepares real-world data for predictive modeling in a statistically sound manner. 'vtreat' prepares variables so that data has fewer exceptional cases, making it easier to safely use models in production. Common problems 'vtreat' defends against: 'Inf', 'NA', too many categorical levels, rare categorical levels, and new categorical levels (levels seen during application, but not during training). 'vtreat::prepare' should be used as you would use 'model.matrix'.

**License** GPL-3

**Imports** stats

**Suggests** testthat, knitr, parallel, rmarkdown, dplyr, ggplot2,  
RSQLite, datasets

**LazyData** true

**VignetteBuilder** knitr

**RoxygenNote** 6.0.1

**ByteCompile** true

**NeedsCompilation** no

**Author** John Mount [aut, cre],  
Nina Zumel [aut],  
Win-Vector LLC [cph]

**Repository** CRAN

**Date/Publication** 2018-01-20 15:32:03 UTC

## R topics documented:

buildEvalSets	2
catScore	4
designTreatmentsC	5
designTreatmentsN	7
designTreatmentsZ	8
format.vtreatment	10
getSplitPlanAppLabels	10
kWayCrossValidation	11
kWayStratifiedY	12
linScore	13
makekWayCrossValidationGroupedByColumn	13
mkCrossFrameCExperiment	14
mkCrossFrameNExperiment	16
oneWayHoldout	18
prepare	19
print.vtreatment	20
problemAppPlan	21
vnames	21
vorig	22
vtreat	22

## Index 23

---

buildEvalSets	<i>Build set carve-up for out-of sample evaluation.</i>
---------------	---

---

### Description

Return a carve-up of `seq_len(nRows)`. Very useful for any sort of nested model situation (such as data prep, stacking, or super-learning).

### Usage

```
buildEvalSets(nRows, ..., dframe = NULL, y = NULL, splitFunction = NULL,
              nSplits = 3)
```

### Arguments

<code>nRows</code>	scalar, $\geq 1$ number of rows to sample from.
<code>...</code>	no additional arguments, declared to forced named binding of later arguments.
<code>dframe</code>	(optional) original data.frame, passed to user <code>splitFunction</code> .
<code>y</code>	(optional) numeric vector, outcome variable (possibly to stratify on), passed to user <code>splitFunction</code> .
<code>splitFunction</code>	(optional) function taking arguments <code>nSplits</code> , <code>nRows</code> , <code>dframe</code> , and <code>y</code> ; returning a user desired split.
<code>nSplits</code>	integer, target number of splits.

## Details

Also sets attribute "splitmethod" on return value that describes how the split was performed. attr(returnValue,'splitmethod') is one of: 'notsplit' (data was not split; corner cases like single row data sets), 'oneway' (leave one out holdout), 'kwaycross' (a simple partition), 'userfunction' (user supplied function was actually used), or a user specified attribute. Any user desired properties (such as stratification on y, or preservation of groups designated by original data row numbers) may not apply unless you see that 'userfunction' has been used.

The intent is the user splitFunction only needs to handle "easy cases" and maintain user invariants. If the user splitFunction returns NULL, throws, or returns an unacceptable carve-up then vtreat::buildEvalSets returns its own eval set plan. The signature of splitFunction should be splitFunction(nRows,nSplits,dframe,y) where nSplits is the number of pieces we want in the carve-up, nRows is the number of rows to split, dframe is the original dataframe (useful for any group control variables), and y is a numeric vector representing outcome (useful for outcome stratification).

Note that buildEvalSets may not always return a partition (such as one row dataframes), or if the user split function chooses to make rows eligible for application a different number of times.

## Value

list of lists where the app portion of the sub-lists is a disjoint carve-up of seq\_len(nRows) and each list as a train portion disjoint from app.

## See Also

[kWayCrossValidation](#), [kWayStratifiedY](#), and [makekWayCrossValidationGroupedByColumn](#)

## Examples

```
# use
buildEvalSets(200)

# longer example
# helper fns
# fit models using experiment plan to estimate out of sample behavior
fitModelAndApply <- function(trainData,applicaitonData) {
  model <- lm(y~x,data=trainData)
  predict(model,newdata=applicaitonData)
}
simulateOutOfSampleTrainEval <- function(d,fitApplyFn) {
  eSets <- buildEvalSets(nrow(d))
  evals <- lapply(eSets,
    function(ei) { fitApplyFn(d[ei$train,],d[ei$app,]) })
  pred <- numeric(nrow(d))
  for(eii in seq_len(length(eSets))) {
    pred[eSets[[eii]]$app] <- evals[[eii]]
  }
  pred
}

# run the experiment
```

```

set.seed(2352356)
# example data
d <- data.frame(x=rnorm(5),y=rnorm(5),
               outOfSampleEst=NA,inSampleEst=NA)

# fit model on all data
d$inSampleEst <- fitModelAndApply(d,d)
# compute in-sample R^2 (above zero, falsely shows a
# relation until we adjust for degrees of freedom)
1-sum((d$y-d$inSampleEst)^2)/sum((d$y-mean(d$y))^2)

d$outOfSampleEst <- simulateOutOfSampleTrainEval(d,fitModelAndApply)
# compute out-sample R^2 (not positive,
# evidence of no relation)
1-sum((d$y-d$outOfSampleEst)^2)/sum((d$y-mean(d$y))^2)

```

---

catScore	<i>return significnace 1 variable logistic regression</i>
----------	---

---

## Description

return significnace 1 variable logistic regression

## Usage

```
catScore(varName, x, yC, yTarget, weights, numberOfHiddenDegrees = 0)
```

## Arguments

varName	name of variable
x	numeric (no NAs/NULLs) effective variable
yC	(no NAs/NULLs) outcome variable
yTarget	scalar target for yC to match (yC==tTarget is goal)
weights	(optional) numeric, non-negative, no NAs/NULLs at least two positive positions
numberOfHiddenDegrees	optional scalar $\geq 0$ number of additional modeling degrees of freedom to account for.

## Value

significance estimate of a 1-variable logistic regression

## Examples

```

d <- data.frame(y=c(1,1,0,0,1,1,0,0,1,1,1,1))
d$x <- seq_len((nrow(d)))
vtreat:::catScore('x',d$x,d$y,1,NULL)

```

---

designTreatmentsC      *Build all treatments for a data frame to predict a categorical outcome.*

---

### Description

Function to design variable treatments for binary prediction of a categorical outcome. Data frame is assumed to have only atomic columns except for dates (which are converted to numeric). Note: re-encoding high cardinality categorical variables can introduce undesirable nested model bias, for such data consider using [mkCrossFrameCExperiment](#).

### Usage

```
designTreatmentsC(dframe, varlist, outcomename, outcometarget, ...,
  weights = c(), minFraction = 0.02, smFactor = 0, rareCount = 0,
  rareSig = NULL, collarProb = 0, codeRestriction = NULL,
  customCoders = NULL, splitFunction = NULL, ncross = 3,
  forceSplit = FALSE, catScaling = FALSE, verbose = TRUE,
  parallelCluster = NULL)
```

### Arguments

dframe	Data frame to learn treatments from (training data), must have at least 1 row.
varlist	Names of columns to treat (effective variables).
outcomename	Name of column holding outcome variable. <code>dframe[[outcomename]]</code> must be only finite non-missing values.
outcometarget	Value/level of outcome to be considered "success", and there must be a cut such that <code>dframe[[outcomename]]==outcometarget</code> at least twice and <code>dframe[[outcomename]]!=outcometarget</code> at least twice.
...	no additional arguments, declared to forced named binding of later arguments
weights	optional training weights for each row
minFraction	optional minimum frequency a categorical level must have to be converted to an indicator column.
smFactor	optional smoothing factor for impact coding models.
rareCount	optional integer, allow levels with this count or below to be pooled into a shared rare-level. Defaults to 0 or off.
rareSig	optional numeric, suppress levels from pooling at this significance value greater. Defaults to NULL or off.
collarProb	what fraction of the data (pseudo-probability) to collar data at if <code>doCollar</code> is set during <a href="#">prepare</a> .
codeRestriction	what types of variables to produce (character array of level codes, NULL means no restriction).

customCoders	map from code names to custom categorical variable encoding functions (please see <a href="https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md">https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md</a> ).
splitFunction	(optional) see vtreat::buildEvalSets .
ncross	optional scalar $\geq 2$ number of cross validation splits use in rescoring complex variables.
forceSplit	logical, if TRUE force cross-validated significance calculatons on all variables.
catScaling	optional, if TRUE use glm() linkspace, if FALSE use lm() for scaling.
verbose	if TRUE print progress.
parallelCluster	(optional) a cluster object created by package parallel or package snow

### Details

The main fields are mostly vectors with names (all with the same names in the same order):

- vars : (character array without names) names of variables (in same order as names on the other diagnostic vectors) - varMoves : logical TRUE if the variable varied during hold out scoring, only variables that move will be in the treated frame - # - sig : an estimate significance of effect

See the vtreat vignette for a bit more detail and a worked example.

### Value

treatment plan (for use with prepare)

### See Also

[prepare](#) [designTreatmentsN](#) [designTreatmentsZ](#) [mkCrossFrameCExperiment](#)

### Examples

```
dTrainC <- data.frame(x=c('a','a','a','b','b','b'),
  z=c(1,2,3,4,5,6),
  y=c(FALSE,FALSE,TRUE,FALSE,TRUE,TRUE))
dTestC <- data.frame(x=c('a','b','c',NA),
  z=c(10,20,30,NA))
treatmentsC <- designTreatmentsC(dTrainC,colnames(dTrainC),'y',TRUE)
dTrainCTreated <- prepare(treatmentsC,dTrainC,pruneSig=0.99)
dTestCTreated <- prepare(treatmentsC,dTestC,pruneSig=0.99)
```

---

designTreatmentsN      *build all treatments for a data frame to predict a numeric outcome*

---

### Description

Function to design variable treatments for binary prediction of a numeric outcome. Data frame is assumed to have only atomic columns except for dates (which are converted to numeric). Note: each column is processed independently of all others. Note: re-encoding high cardinality categorical variables can introduce undesirable nested model bias, for such data consider using [mkCrossFrameNExperiment](#).

### Usage

```
designTreatmentsN(dframe, varlist, outcomename, ..., weights = c(),
  minFraction = 0.02, smFactor = 0, rareCount = 0, rareSig = NULL,
  collarProb = 0, codeRestriction = NULL, customCoders = NULL,
  splitFunction = NULL, ncross = 3, forceSplit = FALSE, verbose = TRUE,
  parallelCluster = NULL)
```

### Arguments

dframe	Data frame to learn treatments from (training data), must have at least 1 row.
varlist	Names of columns to treat (effective variables).
outcomename	Name of column holding outcome variable. <code>dframe[[outcomename]]</code> must be only finite non-missing values and there must be a cut such that <code>dframe[[outcomename]]</code> is both above the cut at least twice and below the cut at least twice.
...	no additional arguments, declared to forced named binding of later arguments
weights	optional training weights for each row
minFraction	optional minimum frequency a categorical level must have to be converted to an indicator column.
smFactor	optional smoothing factor for impact coding models.
rareCount	optional integer, allow levels with this count or below to be pooled into a shared rare-level. Defaults to 0 or off.
rareSig	optional numeric, suppress levels from pooling at this significance value greater. Defaults to NULL or off.
collarProb	what fraction of the data (pseudo-probability) to collar data at if <code>doCollar</code> is set during <a href="#">prepare</a> .
codeRestriction	what types of variables to produce (character array of level codes, NULL means no restriction).
customCoders	map from code names to custom categorical variable encoding functions (please see <a href="https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md">https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md</a> ).
splitFunction	(optional) see <code>vtreat::buildEvalSets</code> .

ncross            optional scalar  $\geq 2$  number of cross validation splits use in rescoring complex variables.

forceSplit       logical, if TRUE force cross-validated significance calculations on all variables.

verbose           if TRUE print progress.

parallelCluster   (optional) a cluster object created by package parallel or package snow

### Details

The main fields are mostly vectors with names (all with the same names in the same order):

- vars : (character array without names) names of variables (in same order as names on the other diagnostic vectors) - varMoves : logical TRUE if the variable varied during hold out scoring, only variables that move will be in the treated frame - sig : an estimate significance of effect

See the vtreat vignette for a bit more detail and a worked example.

### Value

treatment plan (for use with prepare)

### See Also

[prepare](#) [designTreatmentsC](#) [designTreatmentsZ](#) [mkCrossFrameNExperiment](#)

### Examples

```
dTrainN <- data.frame(x=c('a','a','a','a','b','b','b'),
  z=c(1,2,3,4,5,6,7),y=c(0,0,0,1,0,1,1))
dTestN <- data.frame(x=c('a','b','c',NA),
  z=c(10,20,30,NA))
treatmentsN = designTreatmentsN(dTrainN,colnames(dTrainN),'y')
dTrainNTreated <- prepare(treatmentsN,dTrainN,pruneSig=0.99)
dTestNTreated <- prepare(treatmentsN,dTestN,pruneSig=0.99)
```

---

designTreatmentsZ        *Design variable treatments with no outcome variable.*

---

### Description

Data frame is assumed to have only atomic columns except for dates (which are converted to numeric). Note: each column is processed independently of all others.

### Usage

```
designTreatmentsZ(dframe, varlist, ..., minFraction = 0.02, weights = c(),
  rareCount = 0, collarProb = 0, codeRestriction = NULL,
  customCoders = NULL, verbose = TRUE, parallelCluster = NULL)
```

**Arguments**

dframe	Data frame to learn treatments from (training data), must have at least 1 row.
varlist	Names of columns to treat (effective variables).
...	no additional arguments, declared to forced named binding of later arguments
minFraction	optional minimum frequency a categorical level must have to be converted to an indicator column.
weights	optional training weights for each row
rareCount	optional integer, allow levels with this count or below to be pooled into a shared rare-level. Defaults to 0 or off.
collarProb	what fraction of the data (pseudo-probability) to collar data at if doCollar is set during <a href="#">prepare</a> .
codeRestriction	what types of variables to produce (character array of level codes, NULL means no restriction).
customCoders	map from code names to custom categorical variable encoding functions (please see <a href="https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md">https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md</a> ).
verbose	if TRUE print progress.
parallelCluster	(optional) a cluster object created by package parallel or package snow

**Details**

The main fields are mostly vectors with names (all with the same names in the same order):

- vars : (character array without names) names of variables (in same order as names on the other diagnostic vectors) - varMoves : logical TRUE if the variable varied during hold out scoring, only variables that move will be in the treated frame

See the vtreat vignette for a bit more detail and a worked example.

**Value**

treatment plan (for use with prepare)

**See Also**

[prepare](#) [designTreatmentsC](#) [designTreatmentsN](#)

**Examples**

```
dTrainZ <- data.frame(x=c('a','a','a','a','b','b',NA,'e','e'),
  z=c(1,2,3,4,5,6,7,NA,9))
dTestZ <- data.frame(x=c('a','x','c',NA),
  z=c(10,20,30,NA))
treatmentsZ = designTreatmentsZ(dTrainZ, colnames(dTrainZ),
  rareCount=0)
```

```
dTrainZTreated <- prepare(treatmentsZ, dTrainZ)
dTestZTreated <- prepare(treatmentsZ, dTestZ)
```

---

```
format.vtreatment      Display treatment plan.
```

---

### Description

Display treatment plan.

### Usage

```
## S3 method for class 'vtreatment'
format(x, ...)
```

### Arguments

x	treatment plan
...	additional args (to match general signature).

---

```
getSplitPlanAppLabels read application labels off a split plan.
```

---

### Description

read application labels off a split plan.

### Usage

```
getSplitPlanAppLabels(nRow, plan)
```

### Arguments

nRow	number of rows in original data.frame.
plan	split plan

### Value

vector of labels

### See Also

[kWayCrossValidation](#), [kWayStratifiedY](#), and [makekWayCrossValidationGroupedByColumn](#)

**Examples**

```
plan <- kWayStratifiedY(3,2,NULL,NULL)
getSplitPlanAppLabels(3,plan)
```

---

kWayCrossValidation *k-fold cross validation, a splitFunction in the sense of vtreat::buildEvalSets*

---

**Description**

k-fold cross validation, a splitFunction in the sense of vtreat::buildEvalSets

**Usage**

```
kWayCrossValidation(nRows, nSplits, dframe, y)
```

**Arguments**

nRows	number of rows to split (>1).
nSplits	number of groups to split into (>1,<=nRows).
dframe	original data frame (ignored).
y	numeric outcome variable (ignored).

**Value**

split plan

**Examples**

```
kWayCrossValidation(7,2,NULL,NULL)
```

---

kWayStratifiedY	<i>k-fold cross validation stratified on y, a splitFunction in the sense of vtreat::buildEvalSets</i>
-----------------	---

---

## Description

k-fold cross validation stratified on y, a splitFunction in the sense of vtreat::buildEvalSets

## Usage

```
kWayStratifiedY(nRows, nSplits, dframe, y)
```

## Arguments

nRows	number of rows to split (>1)
nSplits	number of groups to split into (<nRows,>1).
dframe	original data frame (ignored).
y	numeric outcome variable try to have equidistributed in each split.

## Value

split plan

## Examples

```
set.seed(23255)
d <- data.frame(y=sin(1:100))
pStrat <- kWayStratifiedY(nrow(d),5,d,d$y)
problemAppPlan(nrow(d),5,pStrat,TRUE)
d$stratGroup <- vtreat::getSplitPlanAppLabels(nrow(d),pStrat)
pSimple <- kWayCrossValidation(nrow(d),5,d,d$y)
problemAppPlan(nrow(d),5,pSimple,TRUE)
d$simpleGroup <- vtreat::getSplitPlanAppLabels(nrow(d),pSimple)
summary(tapply(d$y,d$simpleGroup,mean))
# ggplot(data=d,aes(x=y,color=as.factor(simpleGroup))) +
#   geom_density() + ggtitle('simple grouping')
summary(tapply(d$y,d$stratGroup,mean))
# ggplot(data=d,aes(x=y,color=as.factor(stratGroup))) +
#   geom_density() + ggtitle('y-stratified grouping')

# # And you can (and should) use your own functions or libraries.
# splitFn <- function(nRows,nSplits,dframe,y) {
#   fullSeq <- seq_len(nRows)
#   part <- caret::createFolds(y=y,k=nSplits)
#   lapply(part,
#     function(appi) {
```

```

#           list(train=setdiff(fullSeq, appi), app=appi)
#           })
# }
# pCaret <- splitFn(nrow(d), 5, d, d$y)
# problemAppPlan(nrow(d), 5, pCaret, TRUE)
# d$caretGroup <- vtreat::getSplitPlanAppLabels(nrow(d), pCaret)
# ggplot(data=d, aes(x=y, color=as.factor(caretGroup))) +
#   geom_density() + ggtitle('caret::createFolds grouping')

```

---

linScore	<i>Return in-sample linear stats and scaling.</i>
----------	---

---

### Description

Return in-sample linear stats and scaling.

### Usage

```
linScore(varName, xcol, ycol, weights, numberOfHiddenDegrees = 0)
```

### Arguments

varName	name of variable
xcol	numeric vector of inputs (no NA/NULL/NaN)
ycol	numeric vector of outcomes (no NA/NULL/NaN)
weights	numeric vector of data weights (no NA/NULL/NaN, all>0.0)
numberOfHiddenDegrees	optional scalar $\geq 0$ number of additional modeling degrees of freedom to account for.

### Value

significance estimate and scaling.

---

makeWayCrossValidationGroupedByColumn	<i>Build a k-fold cross validation splitter, respecting (never splitting) groupingColumn.</i>
---------------------------------------	---

---

### Description

Build a k-fold cross validation splitter, respecting (never splitting) groupingColumn.

**Usage**

```
makekWayCrossValidationGroupedByColumn(groupingColumnName)
```

**Arguments**

```
groupingColumnName
      name of column to group by.
```

**Value**

splitting function in the sense of vtreat::buildEvalSets.

**Examples**

```
d <- data.frame(y=sin(1:100))
d$group <- floor(seq_len(nrow(d))/5)
splitter <- makekWayCrossValidationGroupedByColumn('group')
split <- splitter(nrow(d),5,d,d$y)
d$splitLabel <- vtreat::getSplitPlanAppLabels(nrow(d),split)
rowSums(table(d$group,d$splitLabel)>0)
```

---

```
mkCrossFrameCEXperiment
```

```
Run categorical cross-frame experiment.
```

---

**Description**

Builds a [designTreatmentsC](#) treatment plan and a data frame prepared from dframe that is "cross" in the sense each row is treated using a treatment plan built from a subset of dframe disjoint from the given row. The goal is to try to and supply a method of breaking nested model bias other than splitting into calibration, training, test sets.

**Usage**

```
mkCrossFrameCEXperiment(dframe, varlist, outcomename, outcometarget, ...,
  weights = c(), minFraction = 0.02, smFactor = 0, rareCount = 0,
  rareSig = 1, collarProb = 0, codeRestriction = NULL,
  customCoders = NULL, scale = FALSE, doCollar = FALSE,
  splitFunction = NULL, ncross = 3, forceSplit = FALSE,
  catScaling = FALSE, parallelCluster = NULL)
```

**Arguments**

dframe	Data frame to learn treatments from (training data), must have at least 1 row.
varlist	Names of columns to treat (effective variables).
outcomename	Name of column holding outcome variable. dframe[[outcomename]] must be only finite non-missing values.
outcometarget	Value/level of outcome to be considered "success", and there must be a cut such that dframe[[outcomename]]==outcometarget at least twice and dframe[[outcomename]]!=outcometarget at least twice.
...	no additional arguments, declared to forced named binding of later arguments
weights	optional training weights for each row
minFraction	optional minimum frequency a categorical level must have to be converted to an indicator column.
smFactor	optional smoothing factor for impact coding models.
rareCount	optional integer, allow levels with this count or below to be pooled into a shared rare-level. Defaults to 0 or off.
rareSig	optional numeric, suppress levels from pooling at this significance value greater. Defaults to NULL or off.
collarProb	what fraction of the data (pseudo-probability) to collar data at if doCollar is set during <a href="#">prepare</a> .
codeRestriction	what types of variables to produce (character array of level codes, NULL means no restriction).
customCoders	map from code names to custom categorical variable encoding functions (please see <a href="https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md">https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md</a> ).
scale	optional if TRUE replace numeric variables with regression ("move to outcome-scale").
doCollar	optional if TRUE collar numeric variables by cutting off after a tail-probability specified by collarProb during treatment design.
splitFunction	(optional) see vtreat::buildEvalSets .
ncross	optional scalar >=2 number of cross-validation rounds to design.
forceSplit	logical, if TRUE force cross-validated significance calculations on all variables.
catScaling	optional, if TRUE use glm() linkspace, if FALSE use lm() for scaling.
parallelCluster	(optional) a cluster object created by package parallel or package snow

**Value**

list with treatments and crossFrame

**See Also**

[designTreatmentsC](#) [designTreatmentsN](#) [prepare](#)

**Examples**

```

set.seed(23525)
zip <- paste('z',1:100)
N = 200
d <- data.frame(zip=sample(zip,N,replace=TRUE),
                zip2=sample(zip,20,replace=TRUE),
                y=runif(N))
del <- runif(length(zip))
names(del) <- zip
d$y <- d$y + del[d$zip2]
d$yc <- d$y>=mean(d$y)
cC <- mkCrossFrameCExperiment(d,c('zip','zip2'),'yc',TRUE,
                             rareCount=2,rareSig=0.9)
cor(as.numeric(cC$crossFrame$yc),cC$crossFrame$zip_catB) # poor
cor(as.numeric(cC$crossFrame$yc),cC$crossFrame$zip2_catB) # better
treatments <- cC$treatments
dTrainV <- cC$crossFrame

```

---

mkCrossFrameNExperiment

*Run a numeric cross frame experiment.*


---

**Description**

Builds a [designTreatmentsN](#) treatment plan and a data frame prepared from `dframe` that is "cross" in the sense each row is treated using a treatment plan built from a subset of `dframe` disjoint from the given row. The goal is to try to and supply a method of breaking nested model bias other than splitting into calibration, training, test sets.

**Usage**

```

mkCrossFrameNExperiment(dframe, varlist, outcomename, ..., weights = c(),
                        minFraction = 0.02, smFactor = 0, rareCount = 0, rareSig = 1,
                        collarProb = 0, codeRestriction = NULL, customCoders = NULL,
                        scale = FALSE, doCollar = FALSE, splitFunction = NULL, ncross = 3,
                        forceSplit = FALSE, parallelCluster = NULL)

```

**Arguments**

<code>dframe</code>	Data frame to learn treatments from (training data), must have at least 1 row.
<code>varlist</code>	Names of columns to treat (effective variables).
<code>outcomename</code>	Name of column holding outcome variable. <code>dframe[[outcomename]]</code> must be only finite non-missing values and there must be a cut such that <code>dframe[[outcomename]]</code> is both above the cut at least twice and below the cut at least twice.
<code>...</code>	no additional arguments, declared to forced named binding of later arguments

weights	optional training weights for each row
minFraction	optional minimum frequency a categorical level must have to be converted to an indicator column.
smFactor	optional smoothing factor for impact coding models.
rareCount	optional integer, allow levels with this count or below to be pooled into a shared rare-level. Defaults to 0 or off.
rareSig	optional numeric, suppress levels from pooling at this significance value greater. Defaults to NULL or off.
collarProb	what fraction of the data (pseudo-probability) to collar data at if doCollar is set during <a href="#">prepare</a> .
codeRestriction	what types of variables to produce (character array of level codes, NULL means no restriction).
customCoders	map from code names to custom categorical variable encoding functions (please see <a href="https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md">https://github.com/WinVector/vtreat/blob/master/extras/CustomLevelCoders.md</a> ).
scale	optional if TRUE replace numeric variables with regression ("move to outcome-scale").
doCollar	optional if TRUE collar numeric variables by cutting off after a tail-probability specified by collarProb during treatment design.
splitFunction	(optional) see vtreat::buildEvalSets .
ncross	optional scalar $\geq 2$ number of cross-validation rounds to design.
forceSplit	logical, if TRUE force cross-validated significance calculations on all variables.
parallelCluster	(optional) a cluster object created by package parallel or package snow

**Value**

treatment plan (for use with [prepare](#))

**See Also**

[designTreatmentsC](#) [designTreatmentsN](#) [prepare](#)

**Examples**

```
set.seed(23525)
zip <- paste('z', 1:100)
N = 200
d <- data.frame(zip=sample(zip,N,replace=TRUE),
                zip2=sample(zip,N,replace=TRUE),
                y=runif(N))
del <- runif(length(zip))
names(del) <- zip
d$y <- d$y + del[d$zip2]
```

```
d$yc <- d$y>=mean(d$y)
cN <- mkCrossFrameNExperiment(d,c('zip', 'zip2'),'y',
  rareCount=2,rareSig=0.9)
cor(cN$crossFrame$y,cN$crossFrame$zip_catN) # poor
cor(cN$crossFrame$y,cN$crossFrame$zip2_catN) # better
treatments <- cN$treatments
dTrainV <- cN$crossFrame
```

---

oneWayHoldout	<i>One way holdout, a splitFunction in the sense of vtreat::buildEvalSets.</i>
---------------	--

---

### Description

Note one way holdout can leak target expected values, so it should not be preferred in nested modeling situations. Also, doesn't respect nSplits.

### Usage

```
oneWayHoldout(nRows, nSplits, dframe, y)
```

### Arguments

nRows	number of rows to split (integer >1).
nSplits	number of groups to split into (ignored).
dframe	original data frame (ignored).
y	numeric outcome variable (ignored).

### Value

split plan

### Examples

```
oneWayHoldout(3,NULL,NULL,NULL)
```

---

prepare	<i>Apply treatments and restrict to useful variables.</i>
---------	---

---

### Description

Use a treatment plan to prepare a data frame for analysis. The resulting frame will have new effective variables that are numeric and free of NaN/NA. If the outcome column is present it will be copied over. The intent is that these frames are compatible with more machine learning techniques, and avoid a lot of corner cases (NA,NaN, novel levels, too many levels). Note: each column is processed independently of all others. Also copies over outcome if present. Note: treatmentplan's are not meant for long-term storage, a warning is issued if the version of vtreat that produced the plan differs from the version running prepare().

### Usage

```
prepare(treatmentplan, dframe, ..., pruneSig = NULL, scale = FALSE,
        doCollar = FALSE, varRestriction = NULL, codeRestriction = NULL,
        parallelCluster = NULL)
```

### Arguments

treatmentplan	Plan built by designTreatmentsC() or designTreatmentsN()
dframe	Data frame to be treated
...	no additional arguments, declared to forced named binding of later arguments
pruneSig	suppress variables with significance above this level
scale	optional if TRUE replace numeric variables with single variable model regressions ("move to outcome-scale"). These have mean zero and (for variables with significant less than 1) slope 1 when regressed (lm for regression problems/glm for classification problems) against outcome.
doCollar	optional if TRUE collar numeric variables by cutting off after a tail-probability specified by collarProb during treatment design.
varRestriction	optional list of treated variable names to restrict to
codeRestriction	optional list of treated variable codes to restrict to
parallelCluster	(optional) a cluster object created by package parallel or package snow

### Value

treated data frame (all columns numeric- without NA, NaN)

### See Also

[mkCrossFrameCExperiment](#), [mkCrossFrameNExperiment](#), [designTreatmentsC](#) [designTreatmentsN](#) [designTreatmentsZ](#)

**Examples**

```

dTrainN <- data.frame(x= c('a','a','a','a','b','b','b'),
                     z= c(1,2,3,4,5,6,7),
                     y= c(0,0,0,1,0,1,1))
dTestN <- data.frame(x= c('a','b','c',NA),
                    z= c(10,20,30,NA))
treatmentsN = designTreatmentsN(dTrainN,colnames(dTrainN), 'y')
dTrainNTreated <- prepare(treatmentsN, dTrainN, pruneSig= 0.2)
dTestNTreated <- prepare(treatmentsN, dTestN, pruneSig= 0.2)

dTrainC <- data.frame(x= c('a','a','a','b','b','b'),
                     z= c(1,2,3,4,5,6),
                     y= c(FALSE,FALSE,TRUE,FALSE,TRUE,TRUE))
dTestC <- data.frame(x= c('a','b','c',NA),
                    z= c(10,20,30,NA))
treatmentsC <- designTreatmentsC(dTrainC, colnames(dTrainC),'y',TRUE)
dTrainCTreated <- prepare(treatmentsC, dTrainC, varRestriction= c('z_clean'))
dTestCTreated <- prepare(treatmentsC, dTestC, varRestriction= c('z_clean'))

dTrainZ <- data.frame(x= c('a','a','a','b','b','b'),
                     z= c(1,2,3,4,5,6))
dTestZ <- data.frame(x= c('a','b','c',NA),
                    z= c(10,20,30,NA))
treatmentsZ <- designTreatmentsZ(dTrainZ, colnames(dTrainZ))
dTrainZTreated <- prepare(treatmentsZ, dTrainZ, codeRestriction= c('lev'))
dTestZTreated <- prepare(treatmentsZ, dTestZ, codeRestriction= c('lev'))

```

---

```
print.vtreatment      Print treatmentplan.
```

---

**Description**

Print treatmentplan.

**Usage**

```
## S3 method for class 'vtreatment'
print(x, ...)
```

**Arguments**

```
x          treatmentplan
...        additional args (to match general signature).
```

**See Also**

[designTreatmentsC](#) [designTreatmentsN](#) [designTreatmentsZ](#) [prepare](#)

---

problemAppPlan	<i>check if appPlan is a good carve-up of 1:nRows into nSplits groups</i>
----------------	---

---

**Description**

check if appPlan is a good carve-up of 1:nRows into nSplits groups

**Usage**

```
problemAppPlan(nRows, nSplits, appPlan, strictCheck)
```

**Arguments**

nRows	number of rows to carve-up
nSplits	number of sets to carve-up into
appPlan	carve-up to critique
strictCheck	logical, if true expect application data to be a carve-up and training data to be a maximal partition and to match nSplits.

**Value**

problem with carve-up (null if good)

**See Also**

[kWayCrossValidation](#), [kWayStratifiedY](#), and [makekWayCrossValidationGroupedByColumn](#)

**Examples**

```
plan <- kWayStratifiedY(3,2,NULL,NULL)
problemAppPlan(3,3,plan,TRUE)
```

---

vnames	<i>New treated variable names from a treatmentplan\$treatment item.</i>
--------	---

---

**Description**

New treated variable names from a treatmentplan\$treatment item.

**Usage**

```
vnames(x)
```

**Arguments**

x vtreatment item

**See Also**

[designTreatmentsC](#) [designTreatmentsN](#) [designTreatmentsZ](#)

vorig *Original variable name from a treatmentplan\$treatment item.*

**Description**

Original variable name from a treatmentplan\$treatment item.

**Usage**

vorig(x)

**Arguments**

x vtreatment item.

**See Also**

[designTreatmentsC](#) [designTreatmentsN](#) [designTreatmentsZ](#)

vtreat *vtreat: A Statistically Sound 'data.frame' Processor/Conditioner*

**Description**

A 'data.frame' processor/conditioner that prepares real-world data for predictive modeling in a statistically sound manner. 'vtreat' prepares variables so that data has fewer exceptional cases, making it easier to safely use models in production. Common problems 'vtreat' defends against: 'Inf', 'NA', too many categorical levels, rare categorical levels, and new categorical levels (levels seen during application, but not during training). 'vtreat::prepare' should be used as you would use 'model.matrix'.

**Details**

For more information:

- `vignette('vtreat', package='vtreat')`
- `vignette(package='vtreat')`
- Website: <https://github.com/WinVector/vtreat>

# Index

`buildEvalSets`, [2](#)

`catScore`, [4](#)

`designTreatmentsC`, [5](#), [8](#), [9](#), [14](#), [15](#), [17](#), [19](#),  
[20](#), [22](#)

`designTreatmentsN`, [6](#), [7](#), [9](#), [15–17](#), [19](#), [20](#), [22](#)

`designTreatmentsZ`, [6](#), [8](#), [8](#), [19](#), [20](#), [22](#)

`format.vtreatment`, [10](#)

`getSplitPlanAppLabels`, [10](#)

`kWayCrossValidation`, [3](#), [10](#), [11](#), [21](#)

`kWayStratifiedY`, [3](#), [10](#), [12](#), [21](#)

`linScore`, [13](#)

`makekWayCrossValidationGroupedByColumn`,  
[3](#), [10](#), [13](#), [21](#)

`mkCrossFrameCExperiment`, [5](#), [6](#), [14](#), [19](#)

`mkCrossFrameNExperiment`, [7](#), [8](#), [16](#), [19](#)

`oneWayHoldout`, [18](#)

`prepare`, [5–9](#), [15](#), [17](#), [19](#), [20](#)

`print.vtreatment`, [20](#)

`problemAppPlan`, [21](#)

`vnames`, [21](#)

`vorig`, [22](#)

`vtreat`, [22](#)

`vtreat-package (vtreat)`, [22](#)